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A nonparametric analysis of the spatial distribution of *Convolvulus arvensis* in wheat-sunflower rotations

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SUMMARY

This article describes an application of nonparametric regression to study the spatial structure and identify persistent spatial patterns of the perennial weed *Convolvulus arvensis* L. in 4 years of wheat-sunflower crop rotation in Southern Spain. The annual spatial distributions of weed patches over the study field are estimated using local linear regression. These are then used to delimit areas whose infestation is above an economic threshold. In order to identify the areas at the highest risk of weed infestation across years, a multi-year index is developed and mapped. A parametric bootstrap is used to quantify the variability of the multi-year map. In a precision agriculture environment, such maps can be a useful component of a long-term weed management strategy. Copyright © 2006 John Wiley & Sons, Ltd.

KEY WORDS: local polynomial regression; parametric bootstrap; weed management

1. INTRODUCTION

This article describes an application of local linear regression, a popular nonparametric regression method, to the problem of mapping the persistent spatial distribution of the perennial agricultural weed *Convolvulus arvensis* L. in a field over the course of four growing seasons. Local linear regression has been broadly studied in the context of univariate regression, and we refer to Wand and Jones (1995) for an overview. For bivariate local linear regression, Ruppert and Wand (1994) provide the relevant asymptotic theory for the case in which the errors are independently distributed. In the spatial context, this assumption of independence is often not appropriate, and accounting for possible correlation is required for both inference and smoothing parameter selection. For a review of issues related to

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nonparametric regression with correlated errors, see Hart (1996) and Opsomer *et al.* (2001). Recently, Francisco-Fernández and Opsomer (2005) discussed spatial smoothing and proposed a bandwidth selection method that allows for the presence of correlated errors.

C. arvensis, the plant species of interest in the current article, is a perennial weed that infests wheat (*Triticum aestivum* L.) and sunflower (*Helianthus annuus* L.), the main crop rotation in Andalusia (southern Spain). In the context of weed management, an important characteristic of *C. arvensis* is that it produces few viable seeds when growing in competition with agricultural crops, and instead reproduces primarily vegetatively by underground rootstock. As many fields of wheat–sunflower rotations have been converted into no-tillage or reduced tillage, perennial weeds like *C. arvensis* have become more troublesome because they can no longer be reduced in abundance by repeated tillage or cultivation (Liebman *et al.*, 2001). Reduced-tillage and no-tillage productions, which involve modern agricultural techniques aiming to minimize soil erosion and increase soil organic matter, have increased in Spain in the last 10 years and now accounts for 2 million ha of annual crops (Anonymous, 1998).

It is well known that many weed populations have a patchy distribution (Johnson *et al.*, 1996), with aggregated weed patches of varying size and density interspersed with areas with few or no weed seedlings. A weed patch is considered stable if it is consistent in density and location over time (Wilson and Brain, 1991). Stability is important from the perspective of patch management, since knowledge of the location of patches with high weed density can be used to direct weed control in subsequent years. This is especially true for perennial weeds in reduced tillage systems, where ploughing and cultivation are no longer considered acceptable management options and where farmers want to make informed decisions on the precise use of herbicides (Webster *et al.*, 2000).

Currently, herbicides are most often applied to the entire field even though spraying might be unnecessary in some places. An important goal of site-specific weed control is to apply herbicide only in areas where weed density exceeds an economic threshold (ET) (Dammer *et al.*, 1999). Such an approach has the potential for significantly reducing herbicide use, especially if the location of the weed patches could be determined before the weed plants are fully established. The average reduction in herbicide use from site-specific weed control in cereals ranged from 47 to 80 per cent (Heisel *et al.*, 1996a). In maize, Tian *et al.* (1999) realized savings of 42 per cent, and Timmermann *et al.* (2001) reported that with a site-specific weed control an average of 54 per cent of the herbicides could be saved in sugar beet. In sunflower, Jurado-Expósito *et al.* (2003) achieved an average reduction in herbicide cost around 61 per cent if a given herbicide were applied just to the areas exceeding the ET. In order to implement a site-specific herbicide application strategy, a weed patch distribution map is required.

Previous work on the mapping of weed patches includes linear triangulation (Gerhards *et al.*, 1997), polynomial interpolation (Zanin *et al.*, 1998), and kriging. Kriging weighs the average of observed weed densities and is the only of these three approaches that estimates the variance (Cressie, 1993, pp. 183–194; Isaaks and Srivastava, 1989). The adoption of this approach in weed research has been very recent, but has shown to be useful in quantifying the spatial structure of weed populations (González-Andújar *et al.*, 2001; Heisel *et al.*, 1996b; Jurado-Expósito *et al.*, 2003). However, kriging methods used in these applications assume a constant and known trend. When this assumption is violated, model mis-specification bias can result.

In this article, we develop maps for the spatial distribution of *C. arvensis* over the course of the 1999–2002 growing seasons, for a sample of 261 locations at which the number of plants of *C. arvensis* were counted. Using the concept of economic thresholding discussed above, we identify the areas in each annual map where herbicide applications are warranted under a site-specific weed

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control strategy. In addition to the individual year analyses, we will also use a bootstrap-based method to generate a map that shows the probability of being at high risk of infestation across years. Such a map can be used in subsequent years to predict the places that are most likely to be affected by *C. arvensis*. A multi-year map can be useful to formulate and implement site-specific weed control strategies that take the persistent nature of *C. arvensis* infestations into account.

The broader goal of the article is to demonstrate how a combination of nonparametric regression and bootstrap methods can accommodate a variety of modelling and visualization needs in the weed management context. We show how to produce maps that can be based on a variety of customized management criteria, as well as ways to perform assessments of the variability of the estimates and conduct sensitivity analyses.

The organization of the remainder of this article is as follows. Section 2 describes the statistical model and reviews the nonparametric estimator. Section 3 provides information on the study area, the sampling design and measurement techniques used to obtain the data. In Section 4, we describe the results of the data analysis.

2. LOCAL LINEAR REGRESSION FOR SPATIAL DATA

We briefly describe the spatial nonparametric regression model to be used for the *C. arvensis* data. Assume that a set of $\mathbb{R}^3$-valued random vectors, $\{(\boldsymbol{X}_i, Y_i)\}_{i=1}^n$, are observed, where the Y_i are scalar responses variables and the $\boldsymbol{X}_i$ are predictor variables with a common density f and compact support $\Omega \subseteq \mathbb{R}^2$. In this article, we will refer to the $\boldsymbol{X}_i$ as the *locations* corresponding to the Y_i. The relationship between the locations and the responses variable is assumed to be of the form

$$Y_i = m(\boldsymbol{X}_i) + \varepsilon_i, \quad i = 1, 2, \ldots, n, \tag{1}$$

where $m(\boldsymbol{x})$ is an unknown continuous and smooth function,

$$\mathrm{E}(\varepsilon_i|\boldsymbol{X}_i) = 0, \quad \mathrm{Var}(\varepsilon_i|\boldsymbol{X}_i) = \sigma^2,$$

$$\mathrm{Cov}(\varepsilon_i, \varepsilon_j|\boldsymbol{X}_i, \boldsymbol{X}_j) = \sigma^2 \rho(\boldsymbol{X}_i - \boldsymbol{X}_j),$$

with $\rho(\boldsymbol{d})$ continuous, satisfying $\rho(\boldsymbol{0}) = 1$, $\rho(\boldsymbol{d}) =(-\boldsymbol{d})$, and $|\rho(\boldsymbol{d})| \leq 1$, $\forall \boldsymbol{d}$. The presence of the function ρ implies that the observations are spatially correlated. Francisco-Fernández and Opsomer (2005) discuss the asymptotic framework under which a local linear regression estimator for this model is consistent.

The model (1) assumes that the mean of the response variable Y is an unknown smooth function of location, 'masked' by zero-mean (stationary) errors that are subject to spatial correlation. This is in contrast to the kriging model, which typically assumes that the response variable is a simpler (linear or constant) function of location supplemented by spatially correlated noise. In the kriging model, a larger fraction of the observed behaviour of the data is therefore attributed to noise instead of to the underlying mean function. Formally determining which model is in fact correct for the data cannot be done without replication of the data, and in practice, both approaches lead to estimated spatial maps that are similar. However, the interpretation of the map and the accompanying inference statements are different. See Altman (1997) for a discussion.

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The estimator for $m(\cdot)$ at a location $\boldsymbol{x}$ is the solution for α to the least squares minimization problem

$$\min_{\alpha,\boldsymbol{\beta}} \sum_{i=1}^{n} \left\{ Y_i - \alpha - \boldsymbol{\beta}^T (\boldsymbol{X}_i - \boldsymbol{x}) \right\}^2 K_{\boldsymbol{H}}(\boldsymbol{X}_i - \boldsymbol{x}),$$

where $\boldsymbol{H}$ is a 2×2 symmetric positive definite matrix; K is a bivariate kernel and $K_{\boldsymbol{H}}(\boldsymbol{u}) = |\boldsymbol{H}|^{-1} K(\boldsymbol{H}^{-1}\boldsymbol{u})$. The Epanechnikov kernel function $K(\mathrm{x}) = \frac{2}{\pi} \max\{(1 - \|\mathrm{x}\|^2), 0\}$, a common choice for local linear regression, will be used throughout this article. The bandwidth matrix $\boldsymbol{H}$ controls the shape and the size of the local neighbourhood used for estimating $m(\boldsymbol{x})$. The local linear regression estimator can be written explicitly as

$$\hat{m}(\boldsymbol{x}) = \boldsymbol{e}_1^T \left(\boldsymbol{X}_x^T \boldsymbol{W}_x \boldsymbol{X}_x \right)^{-1} \boldsymbol{X}_x^T \boldsymbol{W}_x \boldsymbol{Y} \equiv \boldsymbol{s}_{\boldsymbol{x}}^T \boldsymbol{Y}, \tag{2}$$

where $\boldsymbol{e}_1$ is a vector with 1 in the first entry and all other entries 0, $\boldsymbol{Y} = (Y_1, \ldots, Y_n)^T$, $\boldsymbol{W}_x = \mathrm{diag}\{K_{\boldsymbol{H}}(\boldsymbol{X}_1 - \boldsymbol{x}), \ldots, K_{\boldsymbol{H}}(\boldsymbol{X}_n - \boldsymbol{X})\}$, and

$$\boldsymbol{X}_x = \begin{pmatrix} 1 & (\boldsymbol{X}_1 - \boldsymbol{x})^T \\ \vdots & \vdots \\ 1 & (\boldsymbol{X}_n - \boldsymbol{x})^T \end{pmatrix}.$$

This estimator depends on the choice of the values used in the bandwidth matrix $\boldsymbol{H}$. We will base our choice of bandwidth values on the correlation-adjusted generalized cross-validation method of Francisco-Fernández and Opsomer (2005), who showed both asymptotically and through simulations that this method works well for spatially correlated data, as long as the correlation can be reasonably approximated by a smoothly decaying function of distance between locations. While knowledge of the correlation function $\rho(\boldsymbol{d})$ is not required to estimate $m(\boldsymbol{x})$, a parametric form for $\rho(\boldsymbol{d})$ is needed for this bandwidth selection method. Also, valid inference and confidence intervals for $m(\boldsymbol{x})$ that take the correlation into account require a parametrically specified correlation function. This is further explored in Section 4.

3. DESCRIPTION OF DATA

The data were collected during the course of four growing seasons (1999–2002). The four surveys were conducted in a field of about 1.6 ha located at Monclova (La Luisiana, Seville), in Andalusia, southern Spain. The field site was farmer-managed using no-tillage production methods. Wheat (*Triticum aestivum* L.) was sown in 1999 and 2001, and sunflower (*Helianthus annuus* L.) in 2000 and 2002. Conventional herbicides practices for weed control were used. Glyphosate was applied pre-emergence at a rate of 2 L/ha for the control of annual weed seedlings in wheat and sunflower. At these rates, the herbicides had no significant activity on perennial shoots of *C. arvensis*.

Sample measurements of weed density were made in early May before crop harvesting, using a procedure summarized as follows. An area measuring 65 m wide by 250 m long was selected for the intensive survey in 1999, and the same area was sampled again in subsequent years. The survey area was located in a larger field of approximately 40 ha, and its borders were at least 50 m from the main

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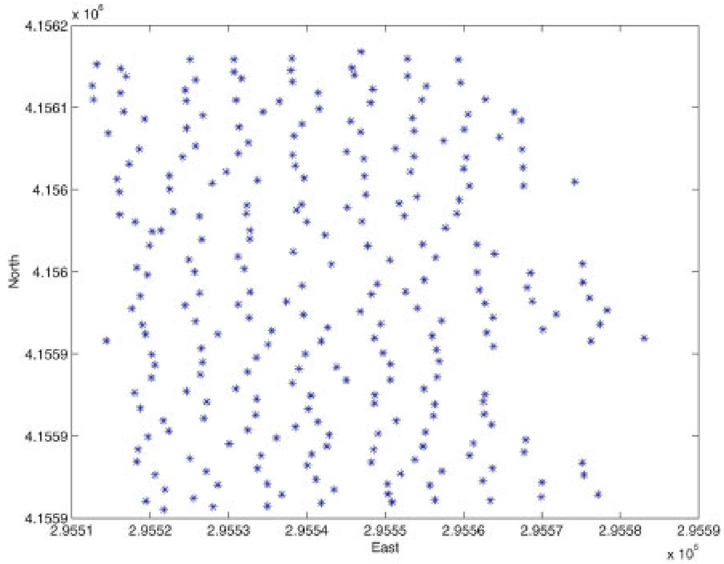

Figure 1. Locations (in UTM East/North coordinates) of *C. arvensis* measurements

borders of the field. Crop rows were always oriented south-north across the study area during the course of the study. *C. arvensis* density assessments were performed following an approximate 7 by 7 m grid pattern, resulting in a total of 261 sampling units. The position of each grid point was georeferenced using a Differential Global Positioning System (DGPS) and recorded in UTM East/North coordinates (in meters). At each node, the number of individual plants of *C. arvensis* were counted in a 2 by 2 m square. Figure 1 shows the 261 locations where the number of plants were counted each year. A portion of the data used in this study were previously studied by Jurado-Expósito *et al.* (2003), where a more detailed description of the study design and measurements is provided.

Based on previous research, the economic threshold (ET), i.e., the *C. arvensis* density causing a reduction in net wheat or sunflower yield equal to the control treatment cost, was estimated at approximately 14 plants/m^2 (Castro-Tendero and García-Torres, 1995). Hence, if a wall-to-wall application of herbicide is to be replaced by a site-specific application, the location of patches of *C. arvensis* with density exceeding ET would represent the optimal application target. For any ET value, it would be possible to produce target herbicide application maps for each year by identifying which parts of the field have estimated weed densities higher than ET. The percentage of annually saved herbicide compared to wall-to-wall application could then readily be estimated from these maps.

In the case of perennial weeds like *C. arvensis*, there is a clear interest not only in locating the high density patches in any given year, but also to determine the location of areas most at risk of multi-year infestations. If those areas in particular can be targeted for treatment, it might be possible to further reduce the long-term of treatment needs for the overall field. Because many factors affecting both the crop and weed growth vary across the years, the size and exact location of *C. arvensis* ‘clumps’ change in character, so that a multi-year map will need to be able to incorporate such heterogeneity.

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While such a map could be based on a wide range of different methods to combine annual estimates, we decided after some experimentation with alternatives to use a relatively simple rule based on ET:

> a field point is considered significantly at risk of infestation if its weed density exceeds the ET in at least 3 of the 4 years.

More complicated rules could certainly be applied, but the main characteristic of interest of this rule is that it does not lead to a statistical estimator with readily quantifiable properties. Hence, we will use it to illustrate the use of bootstrapping and sensitivity analysis in the assessment of customized weed management strategies. In particular, because any ET value is only an approximation that depends on weed management costs and crop market conditions, we will assess how sensitive the results are to the chosen ET value.

4. RESULTS

We begin by fitting the nonparametric regression model (1) to the data from each year separately. In order to produce a map for the survey area of interest, the local linear estimates were computed on a dense regular 200×200 grid overlaying the field. As noted in Section 2, the adjusted GCV method for bandwidth selection of Francisco-Fernáandez and Opsomer (2005) requires the specification of a model for the correlation. We used the exponential model

$$\rho(\boldsymbol{d}) = \exp(-\tau \|\boldsymbol{d}\|) \tag{3}$$

for this purpose, where τ is an unknown parameter, and fitted that model to the residuals of a pilot local linear regression fit. Visual inspection of the plots (not shown) comparing observed and model predicted correlations at a range of distances indicated that the exponential model fitted the data reasonably well. As this model specification is used in the selection of bandwidth values and does not determine the actual shape of the spatial distribution function $m(\boldsymbol{x})$ in (1), modest differences between the true spatial correlation and the assumed correlation model would have a negligible effect on $\hat{m}(\boldsymbol{x})$.

The bandwidth selection method was applied to each of the 4 years individually, and resulted in bandwidth matrices that had similar but not identical characteristics. In order to avoid introducing differences between the years due to the bandwidth, it was decided to use a single bandwidth matrix for all the years, by taking the average of the annual bandwidth matrices. Hence, the bandwidth matrix used for all years was equal to

$$\boldsymbol{H} = \begin{bmatrix} 44.81 & 10.34 \\ 10.34 & 39.41 \end{bmatrix}.$$

This corresponds to a moderate amount of smoothing, since this bandwidth matrix implies that for any location $\boldsymbol{x}$ not on the boundary of the study region, 20–25 per cent of the observations have non-zero weight in the nonparametric regression fit.

Figure 2 shows the estimated weed densities for the 4 years. A visual assessment reveals distinct aggregation of infested areas for all years. The *C. arvensis* populations appear more highly aggregated in sunflowers years (Figure 2, 2000 and 2002) compared to the wheat years, and a higher amount of surface area was free of *C. arvensis* plants in sunflower years. This is consistent with the fact that when

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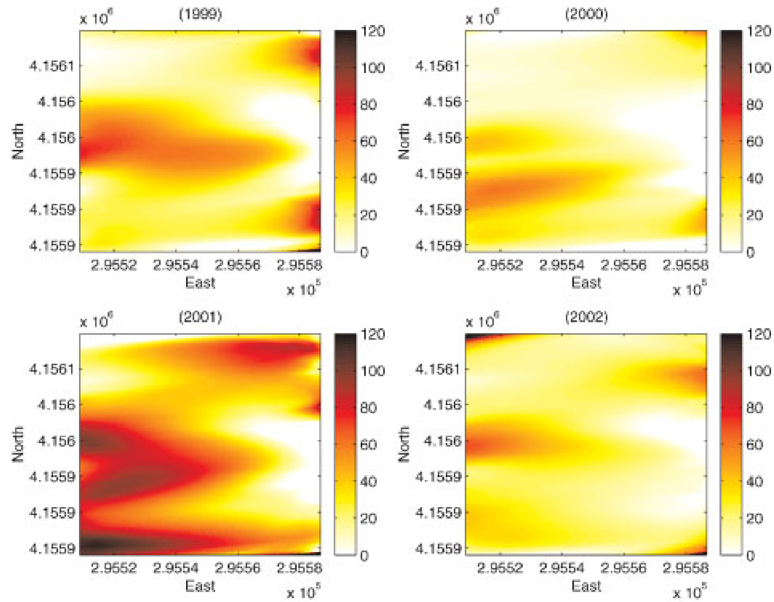

Figure 2. Local linear regression of *C. arvensis* distribution in years 1999–2002 (Plants/m^2)

C. arvensis grows in competition with sunflower, its patches are less numerous and smaller than as compared with wheat (Jurado-Expósito *et al.*, 2005). For any location $\boldsymbol{x}$ in a field in a given year, it is possible to construct an asymptotically correct confidence interval for the local linear regression estimator $\hat{m}(\boldsymbol{x})$, by using the asymptotic normality assumption and the estimated variance–covariance matrix of the data under the assumed correlation model (3) and homoskedasticty. See Lindström *et al.* (2005) for an example of this approach. We skip this step here, and will instead perform a variability assessment using bootstrapping methods after constructing a multi-year map (see below).

If we wanted to apply annual location-specific herbicide treatments to this field using the proposed ET value as a guide, Figure 3 displays which areas would need to be treated at the threshold value of 14 plants/m^2 mentioned in the previous section. As these maps show, a large fraction of the field would have to be treated every year except for the year 2000. Specifically, for ET = 14, the fractions of the surface area that would have to be treated annually according to this rule are estimated to be 76.0 per cent in 1999, 52.6 per cent in 2000, 88.3 per cent in 2001 and 78.0 per cent in 2002. As noted earlier, if the areas most prone to weed infestation across all years could be identified, this knowledge could guide weed scouting and management. We therefore implemented the 'at-risk' rule defined in Section 3 for ET = 14, and Figure 4 displays the resulting spatial distribution map.

The above analysis is useful in identifying portions of the field that appear to be most vulnerable to infestation by *C. arvensis* in individual years as well as across years. However, there is no accompanying measure of variability. In particular, the map in Figure 4 is sensitive to locations whose estimated weed densities are highly variable, as is more likely to happen on the boundaries of the study region, or at locations with weed densities close to the ET in any given year. For instance, it is not clear how to interpret the irregular boundary region seen in the South-East corner of Figure 4, or

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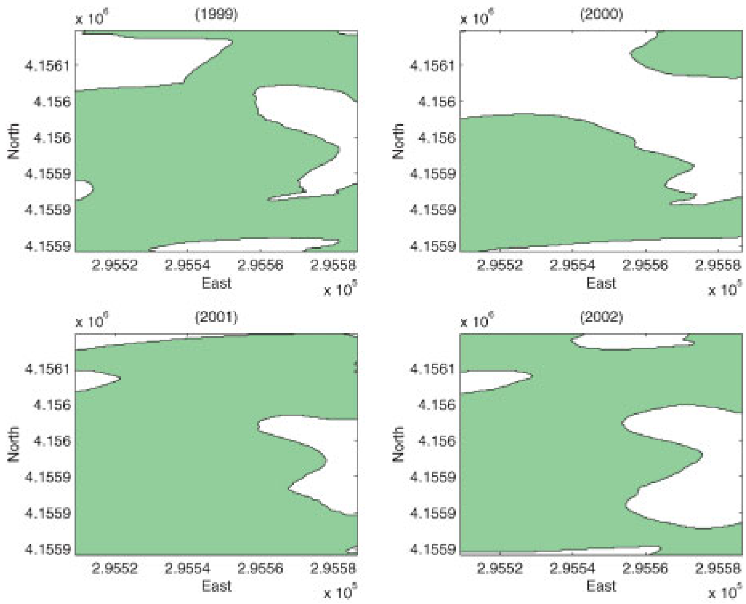

Figure 3. Site-specific herbicide application maps obtained for ET = 14 weeds/m^2; shaded areas are those needing herbicide treatment

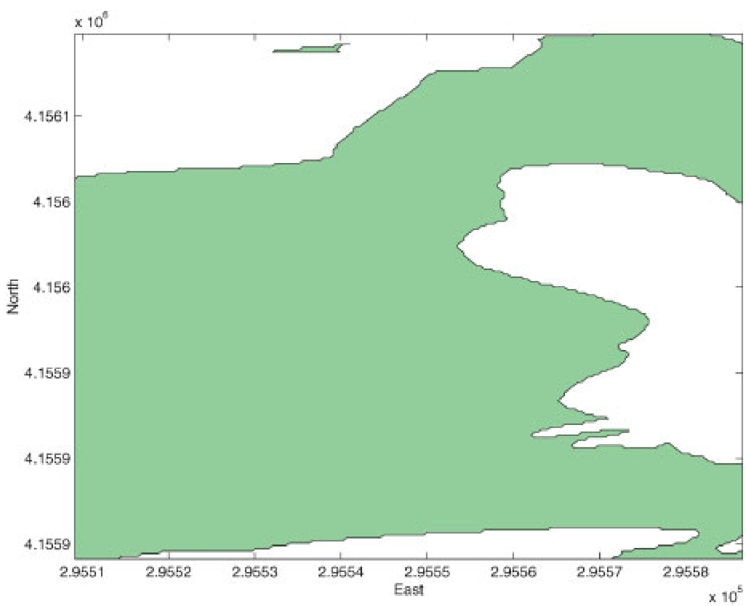

Figure 4. Multi-year map of areas at risk (shaded) and not at risk (white) of persistent *C. arvensis* infestation, for ET = 14 weeds/m^2

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the small area in the center top of the plot. Unlike for the assessment of the variability of the estimated surfaces in Figure 2, there is no readily available method to provide uncertainty estimates for the surface shown in Figure 4.

In order to incorporate variability assessments in this analysis, we extended the parametric bootstrap for correlated data discussed in Vilar-Fernández and González-Manteiga (1996). For each year, a bootstrap dataset is generated by taking the estimated mean spatial surface $\hat{m}(\boldsymbol{x})$ (as shown in Figure 2), and adding bootstrap errors generated as a spatially correlated set of errors. The annual bootstrap errors are obtained by the following steps: (1) fit a homoskedastic exponential model to the residuals from the original regression for that year and obtain parameter estimates, (2) using the Cholesky decomposition of the variance–covariance matrix obtained with the estimates in step 1, transform the original residuals so that they are approximately independent and identically distributed, (3) draw initial bootstrap errors with replacement from the transformed residuals, and (4) transform the initial bootstrap errors back so that their variance–covariance matrix matches that of the original residuals, using the Cholesky decomposition obtained in step 2. This procedure relies on model assumptions for the variance–covariance matrix of the errors, but does not require the full distribution of the errors to be known since it relies on resampling of (transformed) residuals. As an alternative to this procedure, it would also be possible to use the estimates obtained in step 1 above as parameters in a known parametric family (e.g. Gaussian), and generate correlated bootstrap samples directly from that distribution. We do not explore this further here.

Once the annual bootstrap datasets are obtained, the above annual nonparametric regressions are repeated for each bootstrap sample using the same bandwidth $\boldsymbol{H}$ as for the original analysis, and a bootstrap map of at-risk areas as in Figure 4 is produced. This process is repeated 1000 times. The result is the map in Figure 5, which displays the frequency, across bootstrap replicates, for each

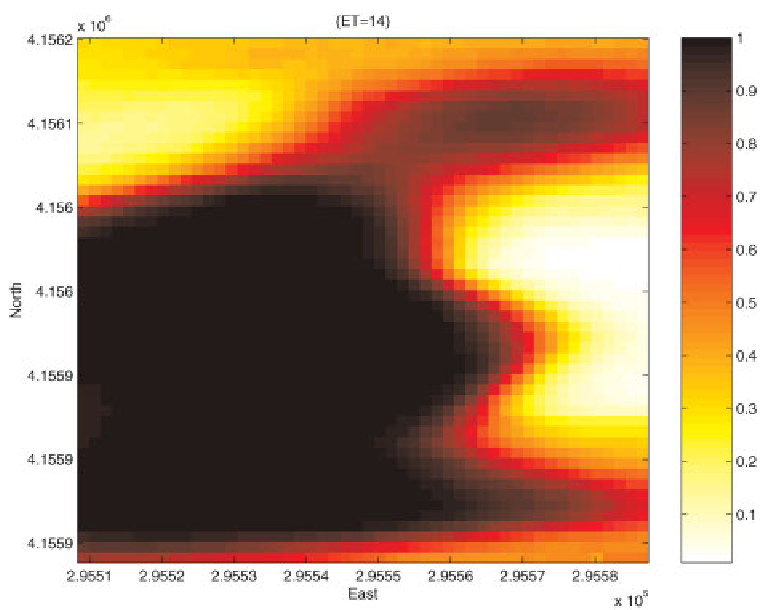

Figure 5. Map with pointwise bootstrap probabilities of being considered at risk of infestation

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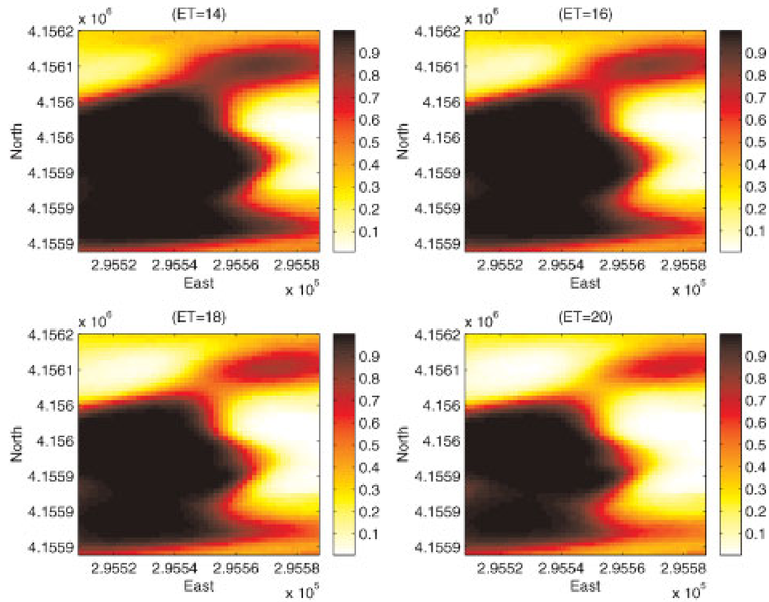

Figure 6. Map with pointwise bootstrap probabilities of being considered at risk of infestation, for different values of the economic threshold

location of how often that location is included in the at-risk area. This analysis indicates that the area of most concern in this field is primarily the South-West quadrant of the field, while the areas stretching in the North-East and South-East observed in Figure 4 have become somewhat 'fainter', in the sense that their probability of being at risk are estimated to be lower.

Finally, in order to evaluate the sensitivity of this procedure to the choice of ET, we repeated the complete analysis for different values of the threshold. Figure 6 compares the results obtained for $\mathrm{ET} = 14$ to those for $\mathrm{ET} = 16$, 18 and 20. The main difference is that the overall area of concern decreases in size as ET is set at higher values, with the North-East and South-East components almost completely disappearing for higher ET, while the South-West quadrant continues to be identified as the main problem area. Hence, even across different values for ET, the South-West quadrant appears to be identifies as the primary area of concern and an important target for more intensive weed management practices.

5. CONCLUSION

In this article, we have developed a method for displaying the portion of a field that is at risk for infestation by perennial weeds, through a combination of nonparametric regression and economic thresholding. A parametric bootstrap was used to estimate the variability of the estimates, and can also be viewed as an estimate of the likelihood to be at risk for infestation. Our method used an economic threshold on weed patch density to determine what constitutes an 'at risk' location as well as a

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heuristic rule to combine data from different years. Both of these features of our method could be extended or customized for different situations, for instance by having different thresholds for different crops or by replacing the multi-year measure by a different type of thresholding altogether. More generally, the overall approach of spatial smoothing and bootstrap-based density mapping provides a useful and flexible set of statistical tools with which to visualize and analyse spatial distribution data.

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